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A SIMULATION ANALYSIS FOR RANKING AND SELECTING THE BEST COMBINATION OF PRODUCTION PLANNING AND ACCOUNTING CONTROL SYSTEMS

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W. Thomas Lin¹

Hubert J. Chen²

Edward J. Dudewicz³

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Associate Professor, School of Accounting, University of Southern California, Los Angeles, California 90007, USA.

²Associate Professor, Department of Statistics and Computer Science, The University of Georgia, Athens, Georgia 30602, USA.

³Professor, Department of Statistics, The Ohio State University, Columbus, Ohio 43210, USA. Supported in part by the Office of Naval Research, Contract No. N00014-78-C-0543.

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A SIMULATION ANALYSIS FOR RANKING AND SELECTING THE BEST COMBINATION OF PRODUCTION AND ACCOUNTING CONTROL SYSTEMS

ABSTRACT

Frequently, the objective of computer simulation experiments of accounting and business systems is to find the best policy, procedure, or decision rule. Previous accounting or business simulation studies assumed that observations taken from each population were normally distributed with unknown means and known or equal variances. Unfortunately, only in rare cases can such assumptions be expected to hold. This paper introduces a multiple-ranking procedure, which allows for unknown and unequal variances, to analyze simulations of production planning and accounting control systems. The model under study is a hypothetical firm with profit and sales as multiple objectives. Two multiple objective planning models with uncertain demands are formulated, and two accounting variance analysis techniques are used and incorporated into the two planning models. A two-stage sampling procedure is used to determine the sample size. The simulated data are analyzed by a multipleranking procedure and then the best policy with respect to profit and sales is selected separately. Possible accounting and business applications are also mentioned.

A multiple-ranking procedure is a statistical process which controls the specific probability of correctness in selecting the best alternative. Although a fundamental multiple-ranking procedure was developed nearly thirty years ago by Bechholfer [1954], decision scientists and accountants have shown little interest in this technique. The two major reasons are that previous multiple-ranking procedures: (1) were developed primarily for scientific experimentation, and (2) assumed that the observations taken from each population are normally distributed with unknown means and known or equal variances, a situation which rarely exists for accounting and business situations.

With the advent of computer simulation techniques, complex business systems can be studied via controlled experiments. The recent development of multiple-ranking procedures with unknown and unequal variances by Dudewicz [1972] and Dudewicz and Dalal [1975] provides a solution for simulation experiments under the unknown and unequal variances.

Oftentimes managers, decision scientists, and accountants face the situation of selecting the best alternative from among a number of policies, procedures, or decision rules. Multiple-ranking procedures offer a useful approach to this kind of decision. The purpose of this paper is to introduce a multiple-ranking procedure with unknown and unequal variances and apply it to analyze simulations of multiple objective production planning and accounting control systems.

The paper begins with the background and purpose of the study. The second section reviews different multiple-ranking procedures with various assumptions about population variances. It is followed by a description of Dudewicz and Dalal's heteroscedastic multiple-ranking procedure. Then

an accounting system design problem for a multiple objective firm is used as an illustration. This model forms the basis for computer simulation experiments and analysis using a multiple-ranking procedure with unknown and unequal variances. Finally, possible accounting and business applications are presented.

MULTIPLE-RANKING PROCEDURES

In accounting and business experiments, frequently a decision to select the best policy, procedure, or decision rule must be made. For example, given more than two machines, the one which will produce the highest mean output per year is sought; or, from among more than two inventory valuation methods being simulated on a computer, the one resulting in the highest mean profit is desired. A conventional F-test, that assumes that population means are equal, does not provide adequate information to decision makers. For example, Conway [1963, p. 531] stated that " . . . the analysis of variance seems a completely inappropriate approach to these problems. It is centered upon the test of the hypothesis that all of the alternatives are equivalent. Yet the alternatives are actually different and it is reasonable to expect some difference in performance, however slight. Thus, the failure to reject the null hypothesis only indicates that the test was not sufficiently powerful to detect the differences - e.g., a longer run would have to be employed. Moreover, even when the investigator rejects the hypothesis, it is highly likely that he is more interested in identifying the best alternatives than in simply concluding that the alternatives are not equivalent. Recently proposed ranking procedures . . . seem more appropriate to the problem than the conventional analysis of variance techniques "

Multiple-ranking procedures can not only handle the problem of ranking alternatives and selecting among them based on empirical results obtained by real-world experiments or computer simulation experiments, but also can design an experiment in advance and determine the sample size. The easiest way of ranking the set of policies is to rank the sample means associated with the given policies. But sample rankings may result in incorrect rankings because of random errors. Given a specified desired probability of correct selection, multiple-ranking procedures can correctly rank the given policies with the desired probability whenever the difference between the highest and the second highest population means is greater than a specified value.

Bechhofer [1954], has developed a single-sample procedure for ranking means of normal populations with known variances. Dunnett [1960] and others also discussed ranking procedures under the assumption of known and equal variances. Zinger and St. Pierre [1958] considered the case of unequal but known variances.

A two-sample (i.e., two-stage) procedure was first proposed by Stein [1945] in the case of one population. Bechhofer, Dunnett and Sobel [1954] applied a two-sample Stein-type solution for the case of unknown but equal variances. Kleijnen and Naylor [1969] discussed some possible approximate procedures for the cases of known and unequal, or unknown and equal, variances. They "... warn the reader against the indiscriminate use of these procedures in cases where the variance in unknown but has been estimated" (p. 610), and note that "further empirical research is definitely needed in order to properly evaluate these approximative techniques" (p. 613).

Dudewicz [1971] has proved that it is impossible to use a singlecample procedure (i.e., a procedure with a fixed size sample or number of
replicate runs) which has a probability of correct selection that is
independent of the variances. Recent work of Dudewicz [1972] and Dudewicz
and Dalal [1975] allows for unknown and unequal variances by using a twosample procedure. A description and the discussion of the superiority of
this procedure is presented in the next section. Their procedure is
suitable for simulations of business and accounting systems because most
of the population variances of these models are unknown and unequal.

A HETEROSCEDASTIC MULTIPLE-RANKING PROCEDURE

In business and accounting simulation applications, one assumes the unknown population variances are equal only due to lack of procedures which can handle the case of unequal unknown variances. For example, Kleijnen and Naylor [1969, pp. 609-610] stated that, "Only in rare cases can the assumption of a common known variance be expected to hold with computer simulation experiments with models of business and economic systems."

The aforementioned Dudewicz [1972] and Dudewicz and Dalal [1975] can be specified as follows:

Assume there are k populations or policies (denoted by π_1 , π_2 , ..., π_k) under consideration, and that π_i yields observations which are normally distributed with unknown mean μ_i and unknown variance σ_i^2 (i = 1, 2,...,k). The experimenter wants to take that number of observations from each population such that the probability of correct selection P(CS) is at least P* (1/k < P* < 1) if the experimenter requires the best mean better than the next best by at least δ * (0 < δ *), i.e., he/she needs to have

 $P(CS) \ge P^* \text{ whenever } \mu_{\left \lfloor k \right \rfloor} = \mu_{\left \lfloor k-1 \right \rfloor} \ge S^*$

where $\mu_{\{k\}}$ and $\mu_{\{k-1\}}$ are population means for the best and the next best populations, respectively. For example, the decision-maker desiring to select the best sales plan among K plans, may wish to be 95% sure (P* = 0.95 here) of a correct selection if the best plan is better than the next best by \$100 (δ * = \$100 here) or more. (Note that δ * and P* are subjective choices by the decision-maker depending on his/her knowledge and experience on the problem of interest.) The procedure has the following four steps:

Step 1: Take an initial sample X_{i1} , . . . , X_{in_0} of size $n_0 \ (\ge 2) \ \text{from population i} \ (\pi_k), \ \text{and calculate the}$ sample mean

$$\bar{X}_{i}(n_{o}) = \sum_{j=1}^{n_{o}} X_{ij} - X_{ij}/n_{o}$$

and sample variance

$$s_i^2 = \sum_{j=1}^{n_o} (X_{ij} - \bar{X}_i (n_o))^2 / (n_o - 1)$$

Step 2: Set the sample size or number of replicate runs n_i by $n_i = \max \{n_0 + 1, \left[\left(\frac{h}{\delta \hat{x}} - S_i \right)^2 \right]$

where [y] denotes the smallest integer \geq y, (i = 1, 2, ..., k). For example, [4.3] = 5, [6.9] = 7, [4] = 4 (since the sample size must be an integer). h is the percentage point which was tabulated by Dudewicz, Ramberg, and Chen [1975].

Step 3: Take $(n_i - n_o)$ additional observations $X_i, n_o+1, X_i, n_o+2, \dots, X_i, n_i$ from the population Π_i ,

and calculate

$$\begin{split} \tilde{Y}_{i}(n_{i} - n_{o}) &= \sum_{j=n_{o}+1}^{n_{i}} X_{ij}/(\tilde{n}_{i} - n_{o}) \quad (i = 1, 2, ..., k) \\ \tilde{\tilde{X}}_{i} &= b_{i} \tilde{X}_{i} (n_{o}) + (1-b_{i}) \tilde{Y}_{i} (n_{i} - n_{o}) \\ &\text{where } b_{i} &= \frac{n_{o}}{n_{i}} (1+\sqrt{1-\frac{n_{i}}{n_{o}}} (1-\frac{n_{i}-n_{o}}{(\frac{h}{\delta^{*}}.S_{i})^{2}})) \\ &(i = 1, 2, ..., k) \end{split}$$

Step 4: Rank order $\tilde{\tilde{X}}_i$ and select the population with the highest of $\tilde{\tilde{X}}_1,\ldots,\tilde{\tilde{X}}_L$.

In essence, this multiple ranking procedure uses a two-stage sampling process to compute the estimated population means, then ranks and selects the population with the highest estimated population mean.

This procedure is superior to any single-stage procedure largely because the probability of correct selection is independent of the unknown variances. This makes it possible to evaluate applicable percentage points in practice while with a single-stage procedure it is impossible to have the probability of correction selection independent of the population variances, hence the probability of correct selection with a single-stage procedure is unknown and such procedures are useless. This result has been stated as a theorem by Dudewicz and Dalal [1975].

To illustrate these results this paper applies Dudewicz and Dalal's multiple-ranking procedure to a simulation of multiple objective production planning and accounting control systems.

AN ILLUSTRATIVE MODEL

With the empirical evidence that firms do not have a single objective of profit maximization, accountants cannot ignore multiple objective decision problems. This paper assumes a hypothetical firm which manufactures and sells two different products, and which has two objectives of profit and sales. The two product-mix planning models developed are a satisficing goal programming model and an optimizing multiple objective linear programming model. For performance evaluation, a traditional standard cost accounting variance analysis and an ex post accounting variance analysis are used as two accounting control systems. 1

The main objective of the study is to identify which of the four combinations of planning models and accounting variance analysis systems results in the highest mean value with respect to actual profit and actual sales per period. Using the level of aspiration concept, standard resource input prices and quantities are revised each period. The actual performance is assumed to be affected by the level of aspiration and other unknown random behavioral variables. Level of aspiration is assumed to be stochastically related to past performance and the new planned budget. 2

The overall model of the firm is summarized in Figure 1. This is a complex model. It incorporates behavioral, level of aspiration concepts, quantitative structured mathematical programming techniques with multiple objectives, and two types of accounting variance analysis systems. The management cycle of the firm is divided into the following planning, operation and performance evaluation processes.

INSERT FIGURE 1

The Planning Process

The planning process includes a resource allocation decision which is a multiple objective, uncertain demand, production planning model with labor, warehouse and machine capacity constraints. It fits a modified product-mix model since it adds the following characteristics to a pure product-mix formulation: (1) considers uncertain demand, (2) incorporates inventory level, and (3) allows overtime, idle time, firing, and hiring labor. Two alternative models, a satisficing goal programming with uncertain demand and an optimizing multiple objective linear programming with uncertain demand, are formulated. Both models have the same constraints such as demand, machine capacity, labor resource, overtime limits, and inventory warehouse capacity.

The goal programming model has two additional goal constraints for both profit and sales targets. The objective function is to minimize the penalty weights on deviations from the profit and sales targets. The solution used Lee's [1972] modified simplex algorithm to obtain planned production, inventory and sales quantities.

The multiple objective linear programming model is a vector maximization model with profit and sales objective functions. Belenson and Kepur's [1973] game theory algorithm was used to solve this model.

The Operations Process

Since there is no real decision maker involved in this study, the operations process is based on a series of assumptions and decision rules similar to Demski [1971].

The actual demand quantity is assumed to be normally distributed with a mean which equals the forecasted sales and a pre-specified standard deviation. The actual price is derived by a function similar to the forecasted price function with some information distortion. The actual material price, material usage per output unit, labor wage rate, larger hours per output unit, variable overhead rate, and machine hours per output unit are assumed to be normally distributed with a mean equal to the standard amount adjusted for the level of aspiration change. The actual production quantity is a linear function of the planned quantity and a behavior implementation variation.

The Performance Evaluation Process

The performance evaluation process includes an accounting variance analysis and a transformation function. The accounting variance analysis compares actual results to the standards. There are two approaches to accounting variance analysis: (1) traditional standard cost variance analysis, and (2) Demski's [1967] ex post variance analysis.

A. Traditional Variance Analysis

Traditional standard cost variance analysis compares an ex ante budget, a budget adjusted to the actual activity level, and actual results:

Ex Ante Profit - Actual Profit = (Ex Ante Profit - Adjusted Profit)
+ (Adjusted Profit - Actual Profit)

- = Mix and Volume Variance + Price and Efficiency Variance
- + Fixed Cost Variance

The price and efficiency variance can be divided into a sales price variance, a materials price variance, a materials usage variance, a labor

wage rate variance, a labor efficiency variance, a variable overhead spending variance, and a variable overhead efficiency variance.

B. Ex Post Variance³

Demski's ex post variance analysis can be expressed as follows:

Ex Ante Profit - Actual Profit = (Ex Ante Profit - Ex Post Profit)

+ (Ex Post Profit - Actual Profit)

- = Forecasting Variance + Opportunity Cost Variance
- + Fixed Cost Variance

Opportunity cost variance can be divided into a mixed and volume variance, and a price efficiency variance.

The transformation function is a stochastic process to characterize the <u>influences</u> of this period's ex ante planned profits, sales, resource price, and quantity standards together with last period's accounting variance analysis results and the weighted average of past performance on this period's actual production quantities, resource prices and quantities.

There are two factors in this study: planning and accounting variance analysis. Response variables are average actual profits per period and average actual sales per period. The four treatment combinations are:

Mode 1 - using goal programming planning model and traditional variance analysis model

SIMULATION ANALYSIS

With simulation, the decision-maker can examine a model under a variety

of contingencies. In this way, the model can be analyzed without

costly experimentation of field or case studies.

- Mode 2 using goal programming planning model and ex post variance analysis model
- Mode 3 using multiple objective linear programming

 planning model and traditional variance analysis

 model
- Mode 4 using multiple objective linear programming planning model and ex post variance analysis model

Since the decision is production planning, a two year run is sufficient for the manager to make short-run decisions. The planning period is assumed to be a month. For each sample (i.e., replication run), the total run length is twenty-four periods.

Following is the simulation result of Dudewicz's and Dalal's [1975] two-stage sampling procedure:

Step 1: Take an initial sample of size 30 replications from mode i (π_i) and calculate sample means and sample variances for actual profit per period, and actual sales per period, respectively.

The sample means and variances for two response variables and 30 replications are shown in Table 1.

Table 1. Initial Sample Means and Variances

 $(n_0 = 30)$

Variables		Mode 1	Mode 2	Mode 3	Mode 4
Actual Profit	Mean	762	792	812	812
Per Period:	Variance	12309	11794	10078	10096
Actual Sales	Mean	6220	6364	6539	6537
Per Period:	Variance	38682	33591	39816	37998

where:

Mode 1 = Goal Programming with Traditional Variance
Analysis

Mode 2 = Goal Programming with Ex Post Variance Analysis

Mode 3 = Multiple Objective Linear Programming with Traditional Variance Analysis

Mode 4 = Multiple Objective Linear Programming with Ex Post Variance Analysis

Step 2: For the multiple-ranking precedures, the sample size of number of replicate runs (n_i) for each mode i is determined by

$$n_i = \max_j n_{ij} = \max_j \max \{31, \left[\frac{h}{\delta^*} S_{ij}\right]^2\}$$

where j = the response variable number, j = 1, 2 h, δ^* and S_{ij} are described in the previous section. From the Dudewicz, Ramberg and Chen [1975] tables, if the least sample difference to be detected for all response variables is taken to be as in Table 2, and the confidence level is at least 95%, h is 3.03 for 4-mode comparisons or rankings. By this choice, we can be sure that we are 95% correct in selecting the best alternative in Table 3.

Table 2. Specified Value of the Least Sample Difference

Variables	The Least Sample Difference $\delta^{\frac{1}{2}}$
Actual Profit Per Period	\$30, or approximately 4% of the average profit
Actual Sales Per Period	\$100, or approximately 1.5% of the average sales

Table 3. Number of Replicate Runs (n_i):
Four-Mode Rankings

Variables	Mode 1	Mode 2	Mode 3	Mode 4
Actual Profit Per Period	126	121	103	103
Actual Sales Per Period	36	31	37	35
n _i = max n _{ij}	126	121	103	103

Step 3: Take (n_i - 30) additional replicate runs from mode i and compute the generalized sample mean \tilde{X}_i which is shown in Table 4.

Step 4 : Select the mode with the highest $\widetilde{\overline{X}}_1$.

Table 4. Multiple-Ranking and Selection (p* = 95%, n_1 = 126, n_2 = 121, n_3 = 103, n_4 = 103)

$\tilde{\bar{\mathbf{X}}}_{\mathbf{i}}$	Actual Profit Per Period	Actual Sales Per Period
Mode 1	\$749	\$6214
Mode 2	779	6363
Mode 3	801	6533
Mode 4	804	6532
Highest	Mode 4	Mode 3
	······································	

The data in Table 4 show that there is not much difference between mode 3 and 4 either in terms of the actual profit or the sales per period. Mode 4 ranks highest in the actual profit per period, while mode 3 ranks highest in the actual sales per period.

Since mode 3 and 4 are very close, a confidence interval on the difference between mode 3 and 4 for the mean actual profit and sales per period is estimated by Dudewicz, Ramberg and Chen's [1975] multiple comparison procedure.

Given k=2 (number of modes for comparison), $n_3=n_4=126$, and assuming that mode 3 is a control mode, one can compute $\tilde{\bar{X}}_3$ and $\tilde{\bar{X}}_4$ by using the first three steps of multiple-ranking procedure. Then the estimated confidence intervals are:

For upper intervals, state that

$$\mu_4 - \mu_3 < (\tilde{\bar{x}}_4 - \tilde{\bar{x}}_3) + \delta *$$

or for lower intervals, state that

$$(\tilde{\bar{x}}_4 - \tilde{\bar{x}}_3) - \delta * < \mu_4 - \mu_3$$

All symbols are defined previously. The estimated confidence intervals are presented in Table 6. $(1 - \alpha)$ is derived from Dudewicz, Ramberg and Chen's Table [1975].

Table 6. Confidence Intervals on the Difference Between Mode 3 and Mode 4 $(1 - \alpha = 95\% \text{ n}_3 = \text{n}_4 = 126)$

Difference	Actual Profit Per Period	Actual Sales Per Period
Prespecified Difference δ*	\$30	\$100
µ ₄ - µ ₃ ≧ or	\$ -28.03 (-3.5%)	\$ -100.80 (-1.5%)
µ ₄ - µ ₃ ≦	\$ 31.97 (4.0%)	\$ 99.20 (1.5%)

The data in Table 6 shows that there is not much difference between mode 3 and 4. Mode 4 is at most \$28.03 lower or at most \$31.97 higher than mode 3 in actual profit per period with a 95% confidence and mode 4 is at most \$100.80 lower or at most \$99.20 higher than mode 3 in actual sales per period with a 95% confidence.

In summary, the results of simulation analysis with a probability of 95% correct selection for the true ranking of the population means are as follows:

- For the simulated profit per period, the ranking sequence is:
 Mode 4 > Mode 3 > Mode 2 > Mode 1 That is, the rankings are:
 (1) Multiple Objective Linear Programming with Ex Post Variance
 Analysis, (2) Multiple Objective Linear Programming with
 Traditional Variance Analysis, (3) Goal Programming with
 Post Variance Analysis, and (4) Goal Programming with
 Traditional Variance Analysis.
- 2. For the simulated sales per period, the ranking sequence is:
 Mode 3 > Mode 4 > Mode 2 > Mode 1

The theory for multivariate multiple-comparisons and ranking procedures has not yet been developed. The results shown in this research are independent comparisons and rankings for each response variable. Given the data in Table 4, mode 4 is the best for profit and mode 3 is the best for sales. There is no conclusion drawn on which mode (mode 3 or 4) should be selected with respect to the two objectives when considered together.

CONCLUSIONS

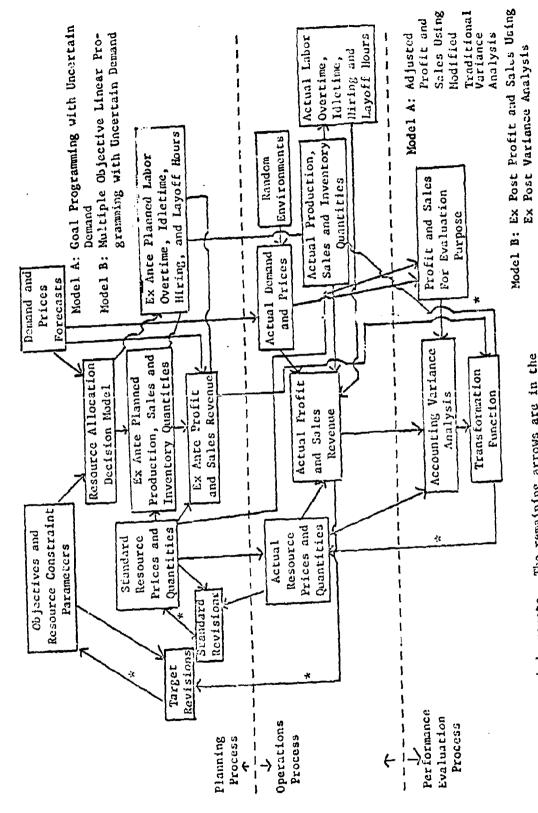
With the aid of a multiple objective firm example, we have attempted to demonstrate an improved multiple-ranking procedure to analyze simulated data which explicitly accounts for unknown and unequal variances. In accounting or business system simulations, the experimenter usually has two objectives in mind: (1) to test whether different system population means are equal or not; if not, a pairwise comparison may be used to find out which one is responsible for the rejection, and (2) to rank and select the best system from all the systems examined. However, the former F-statistics only tell us whether there is a significant difference between two policies (i.e., to satisfy the first objective) under equal variance assumption. The latter, for a specified degree of certainty, indicates the best policy (i.e., to satisfy the second objective). When variances are unequal (unknown), the two-stage procedure is the only available procedure to reach a possible solution.

This paper illustrates a two-stage sampling multiple-ranking procedure which has four steps. The first step is to take an initial sample size from each population and compute sample mean and variance. The second step is to determine optimal sample size by considering the experimenter's minimum probability of correct selection and his/her specified minimum difference between the best and next best population. The third step is to take an additional sample, which is the difference between the optimal sample size and the initial sample size, and compute estimated population means. The last step is to make a selection based on the estimated population means.

From the results of the multiple-ranking procedure based on the simulated output data, one may conclude that the more costly ex post

variance analysis seems indistinguishable from traditional variance analysis, both on sales and profit, if multiple objective linear programming is used (while there is a difference if goal programming is used). Since multiple objective linear programming turned out better than goal programming, one can use cheaper traditional accounting variance analysis with multiple objective linear programming to generate higher sales and profit.

The multiple-ranking procedure can be applied to various accounting and business issues. For example, the LIFO vs. FIFO inventory costing methods can be considered together with the straight-line vs. double-declining balance depreciation methods for a hypothetical firm. The best possible combination, in terms of the highest mean profit or other criteria, can be selected. One also can apply this procedure to select the best job-shop scheduling rule or queueing algorithm. The reader is cautioned, however, to avoid using these techniques without regard for the two assumptions of independence and normality.



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The remainfug arrows are in the For next period amounts. same period. -}*

Figure 1. The Overall Model

FOOTNOTES

- 1. Traditional accounting variance analysis compares an ex ante planned budget, a flexible budget which is adjusted to the actual activity level, and actual results. Ex post accounting variance analysis compares an ex ante planned budget, an ex post optimal budget, and actual results. An ex post optimal budget is the one a firm would have used to determine the ex ante budget had it forecast all model parameters correctly.
- 2. A more detailed description of the ten major behavioral assumptions and the planning and control processes of the simulated firm is given in Lin [1978].
- 3. Lin [1980] developed and illustrated models of ex post analysis under both goal programming and multiple objective linear programming.
- 4. The choice of an initial sample size is based on the discussion of the paper by Bechhofer, Dunnett and Sobel [1954]. The choice of 30 initial sample size is appropriate in this case.

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